Insurance SUMMIT

Process of Developing Predictive Models

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PROCESS OF DEVELOPING PREDICTIVE MODELS

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Process of Developing Predictive Models

- Strategy
- Data Preparation
- Predictive Modeling Techniques
- Building a Generalized Linear Model (GLM)
- Implementation

Strategy

Predictive Analytics Strategy - Considerations

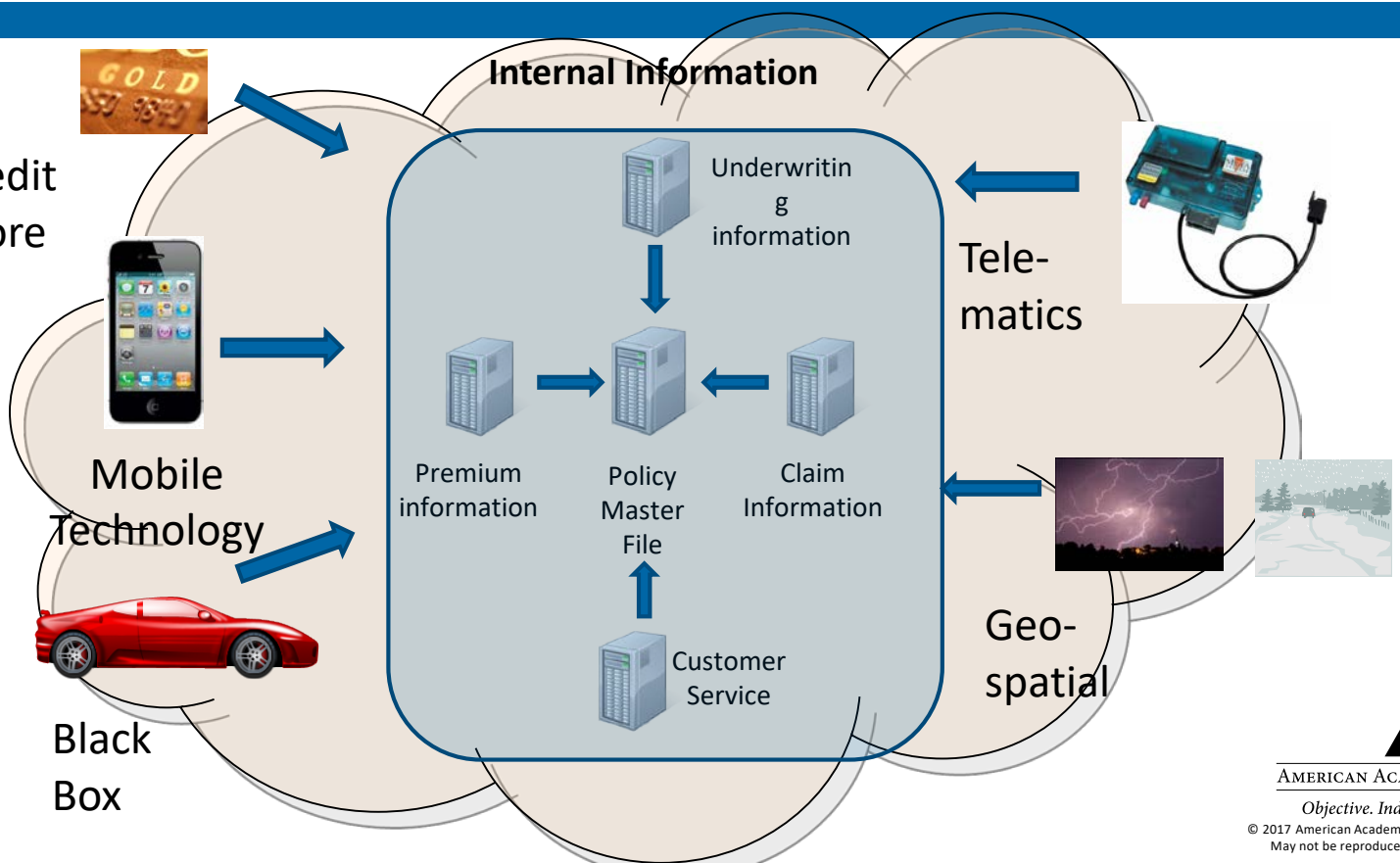
Goals

- Question: What am I trying to accomplish by using predictive analytics?
- Potential answers
  - **Project driven** (I want to develop a new rating plan, I need to detect claim leakage)
  - **Externally driven** (I see a lot written and hear a lot of presentations on predictive analytics)
  - **Defensive** (avoid anti-selection, my competitors are doing it)
  - **Goal driven** (We want to become a data and analytics driven company, we want to use analytics to support our vision – value, enhancing financial security, we want to use analytics to create a competitive advantage)

Predictive Models – One Tool in the Toolkit

Data Preparation

Data is Increasing Exponentially



Challenges Associated with the Expanding Data Universe

- Data historically collected for a number of different purposes – except analytics
- Creates challenges
  - Missing information
  - Incorrect data
  - Significant time required to process data
- Intentional data processing
  - Identify the right data
  - Collect and store data consistently and accurately
  - Prepare data once for multiple applications

Missing/Unknown Values

- Causes
  - Data collection error/issue
  - External data joins
  - Rating plan design
- Potential remedies
  - Collect data
  - Include with a valid level
  - Model as a separate level
  - Imputed values

Accurate Exposure Information

Claim on 5/1/2000

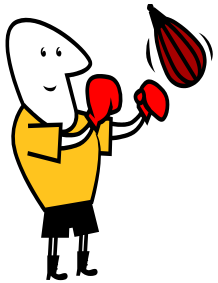
Policy Number	Age	Territory	Symbol	Effective Date	Expiration Date	Transaction Date	Exposure
1	45	10	16	1/1/2000	7/1/2000	1/1/2000	0.50
1	45	10	16	1/1/2000	7/1/2000	4/1/2000	-0.25
1	45	10	19	1/1/2000	7/1/2000	4/1/2000	0.25

Policy Number	Age	Territory	Symbol	Effective Date	Expiration Date	Transaction Date	Exposure
1	45	10	16	1/1/2000	7/1/2000	1/1/2000	0.25
1	45	10	19	1/1/2000	7/1/2000	4/1/2000	0.25

Policy Number	Age	Territory	Symbol	Effective Date	Expiration Date	Transaction Date	Exposure
1	45	10	16	1/1/2000	3/30/2000	1/1/2000	0.25
1	45	10	19	4/1/2000	7/1/2000	4/1/2000	0.25

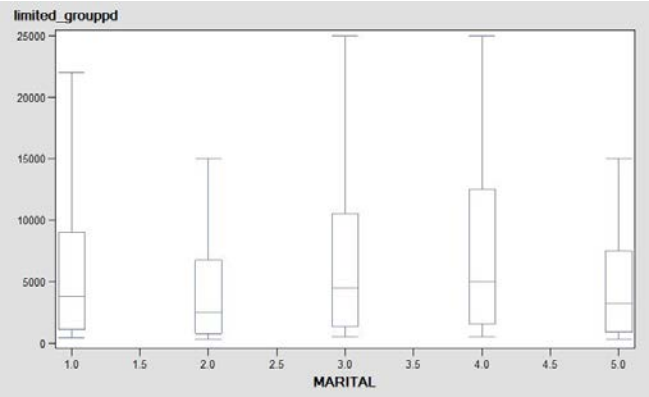
Training/Testing/Validation Data

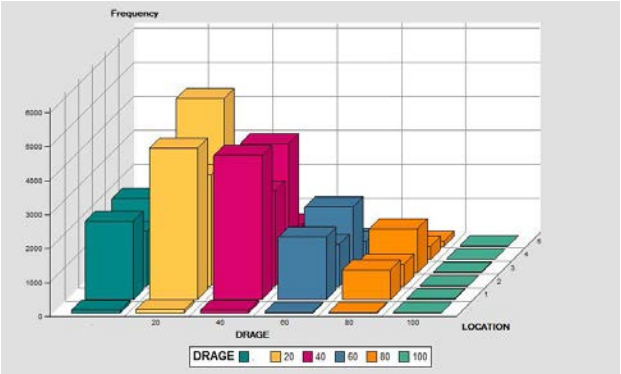
- Develop model with training data
- Test the model developed using testing data
  - Assists in developing optimal model
- Validate final model using validation data
  - Helps decide between competing models
  - Ensures final model is appropriate
- Split percentages
  - Depends on dataset size
- Training and test split only is also acceptable standard practice



Basic Data Summarizations

- Processes used
  - Distribution graphs
  - Simple location measures
  - Two way graphs
  - Data summary tables
- Helps with
  - Understanding
  - Cleaning
  - Potential applications





Predictive Modeling Techniques

- Generalized linear models
- Decision trees
- Gradient boosting
- Neural networks
- Machine Learning
- Ensemble

Machine Learning Overview

Machine Learning

Supervised

- Predictive
- Target Variable
- Task Driven
- Regression, Classification

Unsupervised

- Descriptive
- No Target Variable
- Data Driven
- Clustering, Pattern Discovery, Dimension Reduction

Reinforcement – Algorithm Learns to React

Choice of Models

- Underlying data
- Purpose of the analysis
  - Target variable structure
  - Use of the results
  - Prediction vs. understanding
- Sophistication of user
- Trial and Error
  - Run multiple models and evaluate fit

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Remember the Goal

Response Variable = Systematic Component + Random Component

Signal

Noise

- Find the signal, remove the noise

Overall Mean

Model Complexity (number of parameters)

1 parameter per observation

Underfit

Overfit

- By balancing over- and under-fitting

Not Just One GLM

What characteristics do your exposures have?

What known effects do you want to account for?

$$E[Y_i] = g^{-1}(\Sigma X_{ij} \beta_j + \xi_i)$$

What are you trying to predict?

How does the response variable relate to the predictor variables?

Model output = indicated parameters

- Model output also includes statistics that help a modeler make modeling decisions

Control Variables and Offsets

- Some variables may need to be controlled for in the model
  - Time
  - Geography
- A modeler may want to include known effects in the model as offsets
  - Coverage type variables: limits, deductibles, AOIs
  - Discounts marketed or required to be a certain level
  - Portions of a rating plan not being analyzed

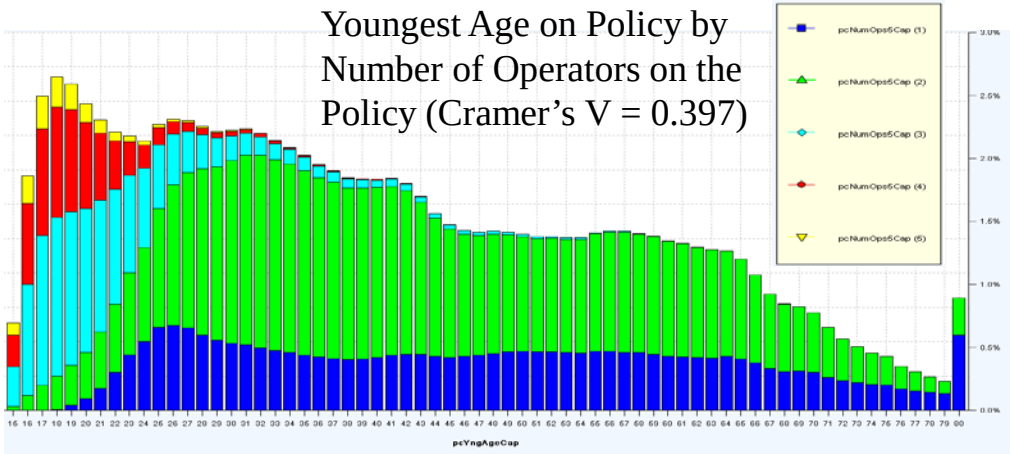
$$E[Y_i] = g^{-1}(\Sigma X_{ij} \beta_j + \xi_i)$$

"It is not generally possible to determine from a single GLM which set of factors are significant since the inclusion or exclusion of one factor will change the observed effects and therefore possibly the significance of other correlated factors in the model. To determine the theoretically optimal set of factors, therefore, it is generally necessary to consider an iterated series of models."

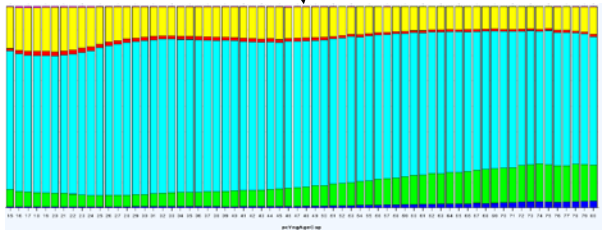
- "The Practitioner's Guide to Generalized Linear Models" (Anderson, D. et al. 2007).

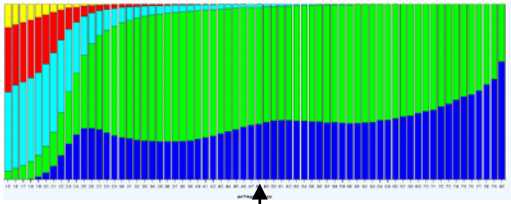
Distributional Bias

Youngest Age on Policy by Number of Operators on the Policy (Cramer's V = 0.397)

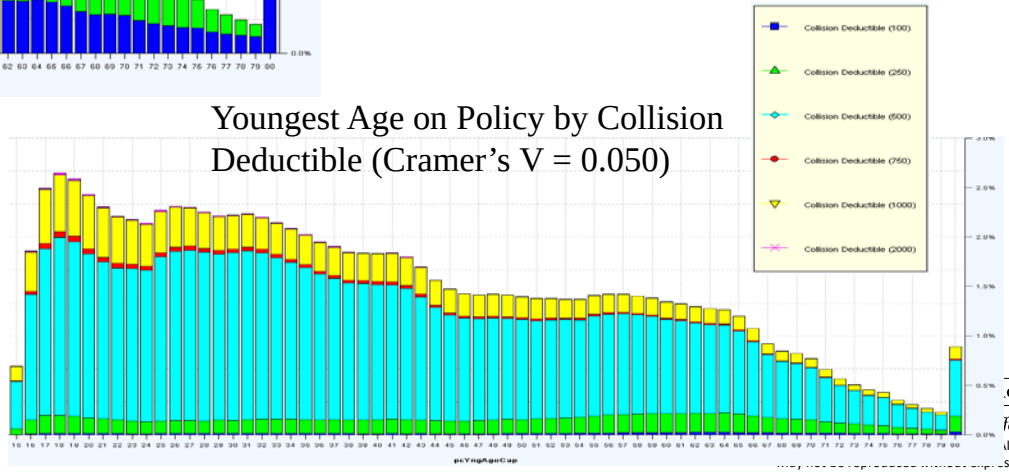


Exposures scaled to 100% show almost no distributional bias



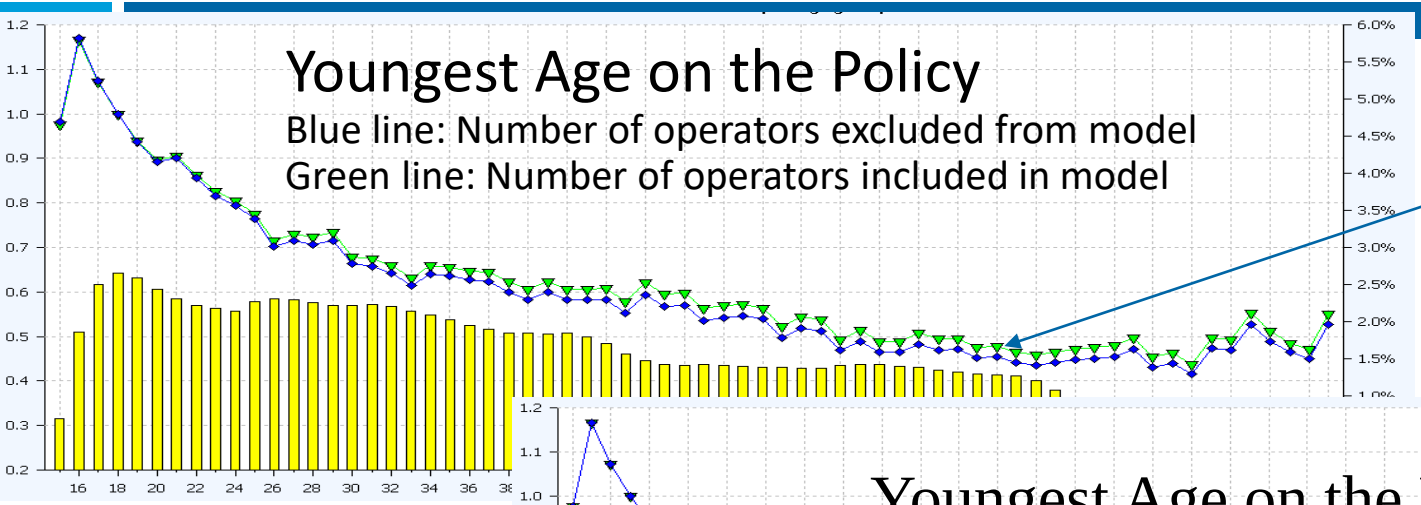


Youngest Age on Policy by Collision Deductible (Cramer's V = 0.050)

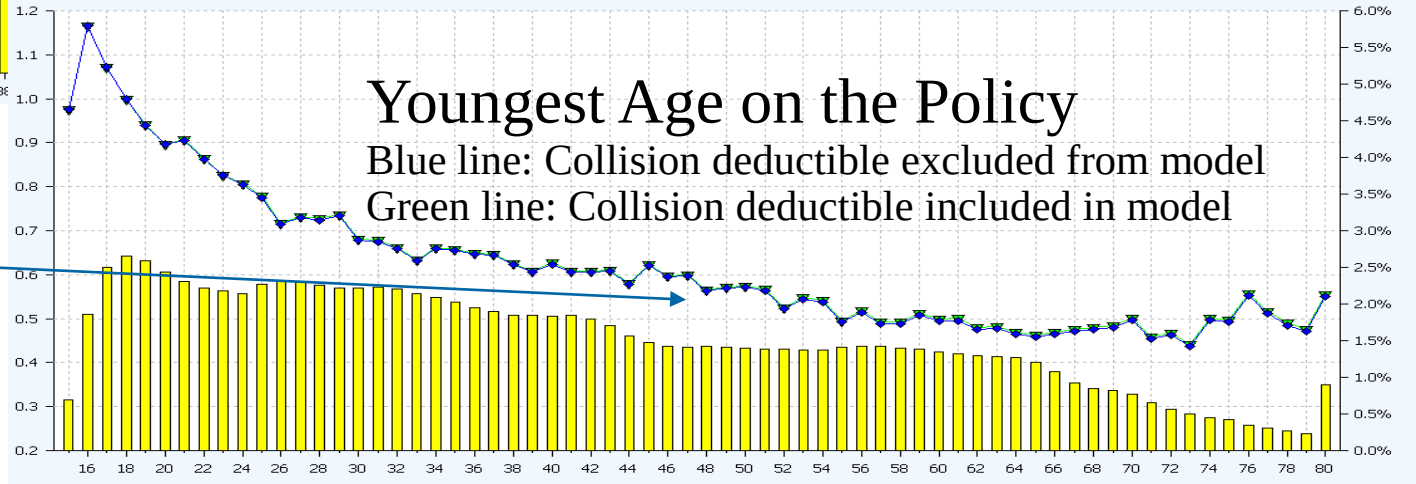


Exposures scaled to 100% show significant distributional bias

Modeling Effect of Distributional Bias



The addition of a correlated variable changes the parameters of the age curve.



The addition of a less correlated variable barely changes the parameters of the age curve.

Variables, Statistics

What characteristics do your exposures have?

What known effects do you want to account for?

$$E[Y_i] = g^{-1}(\Sigma X_{ij} \beta_j + \xi_i)$$

What are you trying to predict?

How does the response variable relate to the predictor variables?

Model output = indicated parameters

- Modelers decide which predictor variables to include, and how to include them
- Statistics are helpful in making decisions, but are not always definitive

Variables, Statistics

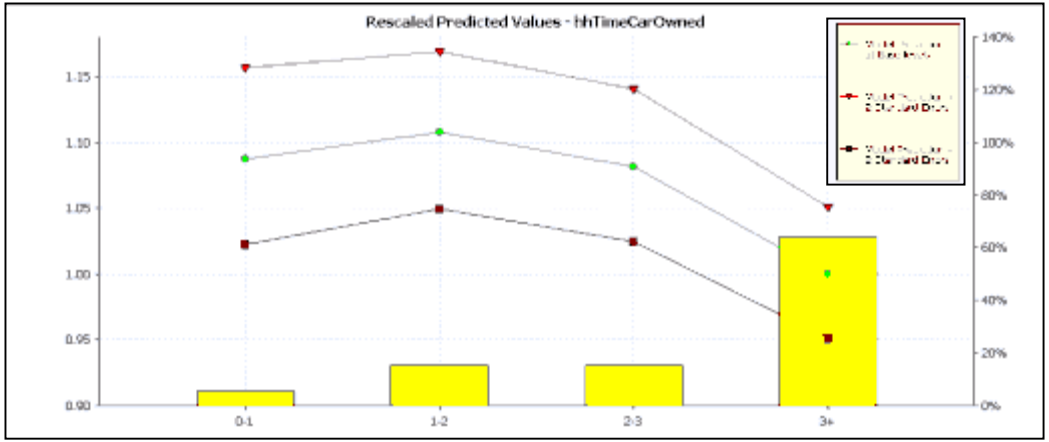
Different modelers may use different approaches or make different modeling decisions on the same data, and both build reasonable models

GLM Diagnostics

A predictor variable should only be included in the model if the variable has a *systematic effect* on the response variable

- How can a modeler tell?
  - Standard errors
  - Type III tests
  - Consistency over time
  - Use of a test dataset

Parameters and Standard Errors



- Simplification:
  - Horizontal line test can inform what levels to group

- Inclusion/Exclusion:
  - If all relativities are close to 1.0 and/or standard errors are wide, it indicates exclusion of a variable

Using only standard errors to make modeling decisions will tend to lead to an under fit model

χ^2 Test

- Use chi test to compare nested models
  - H_0: Two models are basically the same
  - H_1: Two models are statistically different
- If models are the same, use simpler model
- Low χ^2 (~ < 5%): reject H_0

Testing for Inclusion:

Model 1: Base Model

Model 2: Base Model + Var Y

Low χ^2 indicates the models are *not* the same and Var Y is statistically significant.

Testing a Simplification:

Model 1: Base Model w/ Var Y

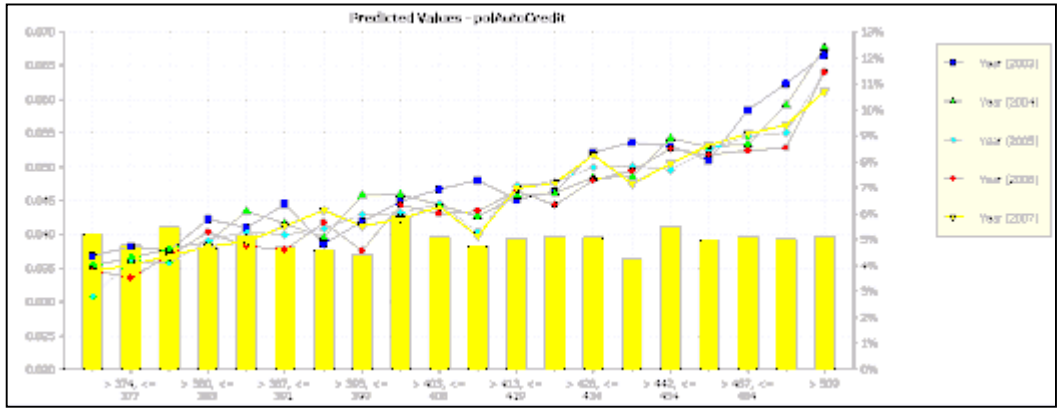
Model 2: Base Model w/ Simplified Var Y

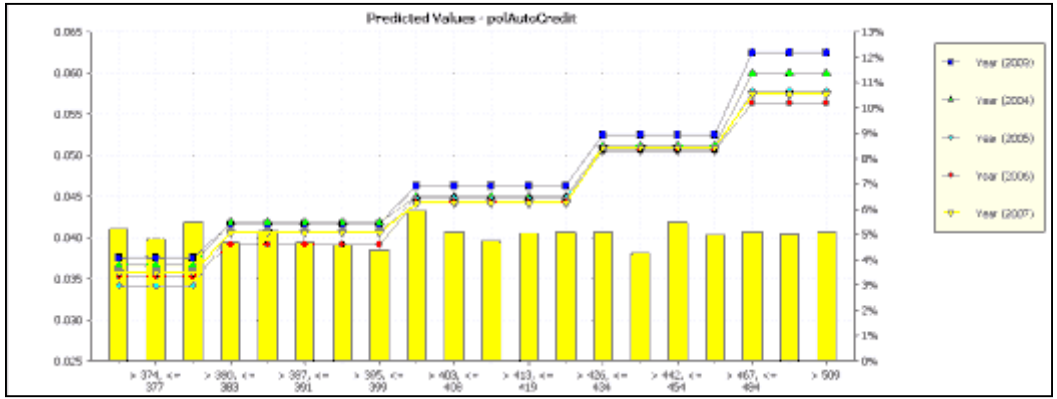
High χ^2 indicates the models are basically the same, so the simplification has not removed significant signal.

Using only χ^2 to make decisions will tend to lead to an over fit model

Consistency

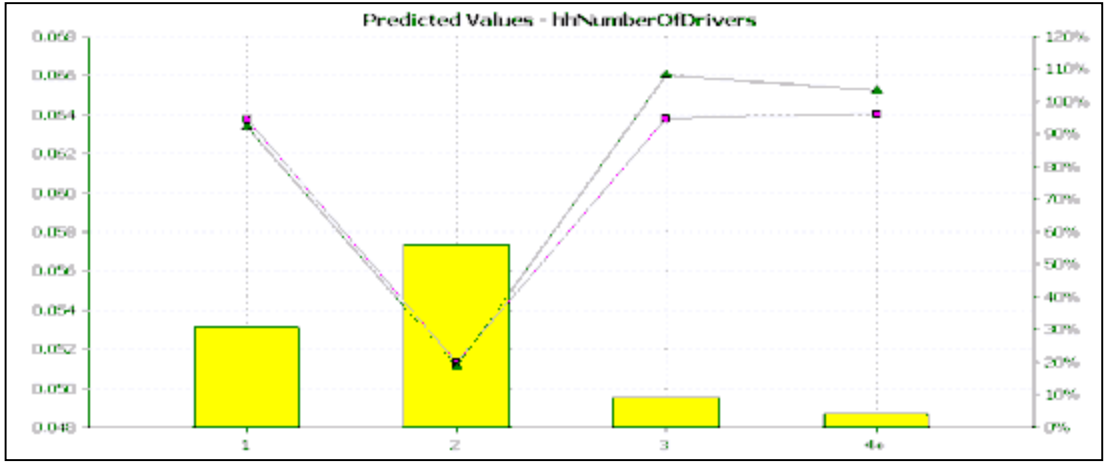
- Inclusion/Exclusion:
  - Looking for similar pattern over different years or subsets of data





- Simplification:
  - Create groups or fit curves to capture consistent trend

Using a Test Dataset

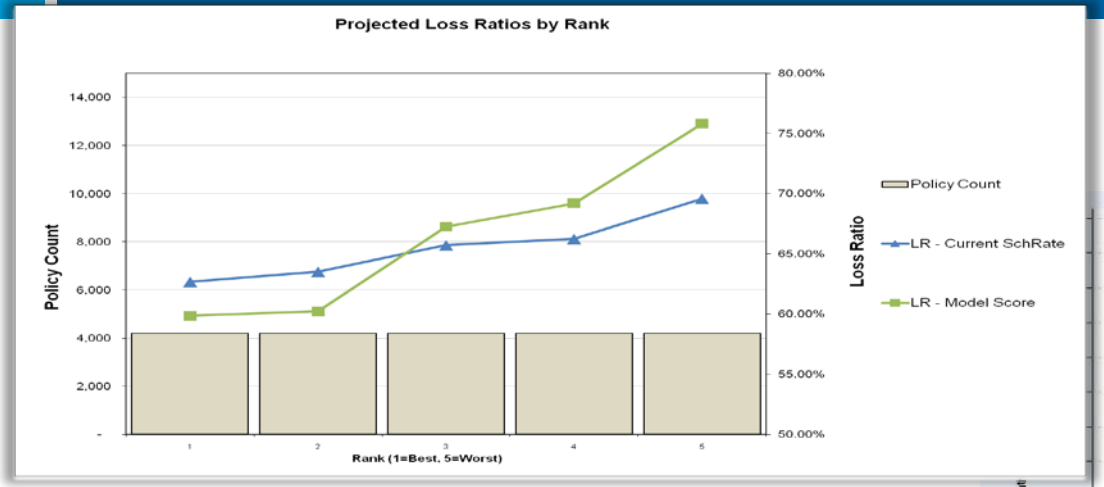


- Balance test
  - Compare actual values to predicted values on a holdout dataset to find areas of systematic imbalance

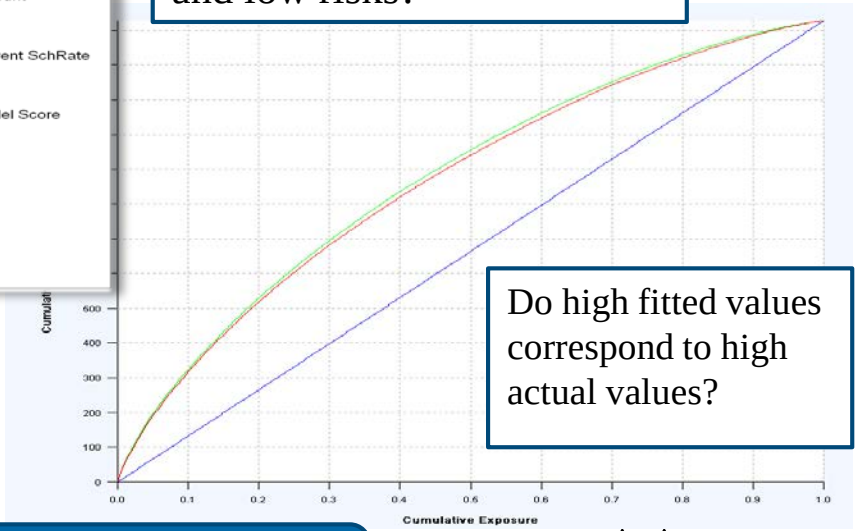
- Stability test
  - Refit model structure on holdout dataset to compare parameters

Use these results to go back and retest specific variables or levels of variables

Model Validation



Which model is better at differentiating between high and low risks?



Do high fitted values correspond to high actual values?

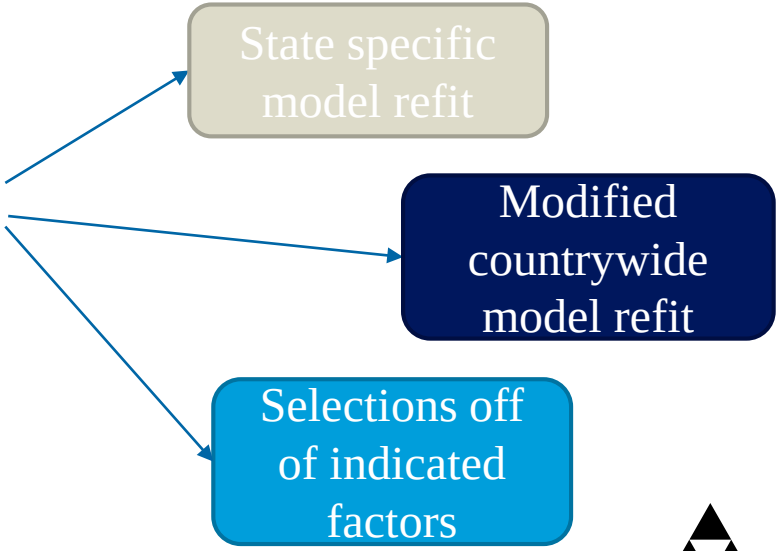
- Score a hold-out dataset with final model parameters
- Actual and predicted values should line up in aggregate

Models can be compared to see which is more predictive, but predictive power is not the only consideration when implementing a model

Model Implementation

Considerations
Regulations
ASOPs
Cost of implementation
Customer impact
Competitive framework
Explainability
Credibility

Potential Actions



Questions

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For More Information

For more information, contact

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